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UNCERTAINTIES IN LCA

A methodology for separating uncertainty and variability in the life cycle greenhouse gas emissions of coal-fueled power generation in the USA

Zoran J. N. Steinmann · Mara Hauck · Ramkumar Karuppiah · Ian J. Laurenzi · Mark A. J. Huijbregts

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Abstract
Purpose Results of life cycle assessments (LCAs) of power generation technologies are increasingly reported in terms of typical values and possible ranges. Extents of these ranges result from both variability and uncertainty. Uncertainty may be reduced via additional research. However, variability is a characteristic of supply chains as they exist; as such, it cannot be reduced without modifying existing systems. The goal of this study is to separately quantify uncertainty and variability in LCA.
Methods In this paper, we present a novel method for differentiating uncertainty from variability in life cycle assessments of coal-fueled power generation, with a specific focus on greenhouse gas emissions. Individual coal supply chains were analyzed for 364 US coal power plants. Uncertainty in CO_2 and CH_4 emissions throughout these supply chains was quantified via Monte Carlo simulation. The method may be used to identify key factors that drive the range of life cycle emissions as well as the limits of precision of an LCA.
Results and discussion Using this method, we statistically characterized the carbon footprint of coal power in the USA in 2009. Our method reveals that the average carbon footprint of coal power (100 year time horizon) ranges from 0.97 to 1.69 kg CO_2eq/kWh of generated electricity (95 % confidence interval), primarily due to variability in plant efficiency. Uncertainty in the carbon footprints of individual plants spans a factor of 1.04 for the least uncertain plant footprint to a factor of 1.2 for the most uncertain plant footprint (95 % uncertainty intervals). The uncertainty in the total carbon footprint of all US coal power plants spans a factor of 1.05.
Conclusions We have developed and successfully implemented a framework for separating uncertainty and variability in the carbon footprint of coal-fired power plants. Reduction of uncertainty will not substantially reduce the range of predicted emissions. The range can only be reduced via substantial changes to the US coal power infrastructure. The finding that variability is larger than uncertainty can obviously not be generalized to other product systems and impact categories. Our framework can, however, be used to assess the relative influence of uncertainty and variability for a whole range of product systems and environmental impacts.

Keywords Carbon footprint · Coal · Electricity generation · Life cycle assessment · Monte Carlo simulation · Uncertainty · Variability

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1 Introduction

Typically, life cycle assessments (LCAs) are conducted by constructing models of each stage and connecting them via material or energy balances. Alternatively, LCAs may be developed top-down using input-output modeling or in a hybrid way combining the two approaches (Williams et al. 2009). Any type of modeling, however, introduces uncertainties. However, not all LCA practitioners take uncertainty into account (Lloyd and Ries 2007). Furthermore, Williams et al. (2009) argue that those who do account for uncertainty

do so inconsistently or incompletely. Part of this may be caused by confusion about the definition and the appropriate way to deal with uncertainty.

Over the years, different classifications of uncertainty and variability in LCA have been developed (EPA 1989; Huijbregts 1998a; Paté-Cornell 1996). An examination of the different frameworks conducted by Heijungs and Huijbregts showed a large overlap among them (Heijungs and Huijbregts 2004). Perhaps the most important distinction is that uncertainty may be reduced by additional research whereas variability may not be reduced. This is because variability reflects real-world differences among alternative life cycles of equivalent products. Variability is caused by systematic differences between individuals (interindividual), processes (technological), and location (spatial), or in time (temporal). This definition of variability is employed by the US EPA (1989) and has been adapted for use in LCA by Huijbregts (1998a). Other authors, e.g., Paté-Cornell (1996), use the term "epistemic" uncertainty to refer to uncertainty caused by incomplete knowledge and "aleatory" uncertainty for true variation that cannot be reduced by additional research. Ergo, aleatory uncertainty is similar to the concept of variability used by the EPA and Huijbregts. In the remainder of this paper, we will use the definition of uncertainty and variability and the further subdivision of these two concepts as used by Huijbregts and the EPA (Huijbregts 1998a, b; Huijbregts et al. 2003).

The implications of variability and uncertainty are different, and thus, it is important to distinguish these two factors (EPA 1989; Huijbregts 1998a). If the range of LCA results is dominated by uncertainty, then more reliable data, more precise emission factors, etc., may be needed before one can robustly conclude that a product has a significantly different environmental impact from another. By contrast, results of LCAs exhibiting a high degree of variability demonstrate true differences among alternative production processes, supply chains, etc. This information can further guide system optimization, product development, or policy.

Three different types of uncertainty are distinguished in this framework for LCA: (1) uncertainty due to lack of knowledge of the "true" value of a model parameter (parameter uncertainty), (2) uncertainty caused by arbitrary choices in a model (decision rule uncertainty), and (3) uncertainty caused by the loss of information resulting from the simplification of reality via models (model uncertainty) (Huijbregts 1998b). Accounting for uncertainty, e.g., via Monte Carlo (MC) simulation, yields multiple output or a distribution of life cycle impacts instead of a single estimate. In addition to these uncertainties, several types of variability may be distinguished for environmental footprinting. For example, differences in the performances of power plants are consequences of variability, as these plants may have different designs, utilize different types of furnaces, get fuel from different sources, or have different types of cooling systems. If an LCA accounts for this variability, many life cycle impacts will result, each corresponding to a unique systematic implementation of the technology.

Electricity plays a vital role in the life cycle of many products. Therefore, it is important to be able to estimate the extent of greenhouse gas (GHG) emissions over the life cycle of electricity generation with as much accuracy and precision (i.e., as close to the actual value and with the smallest range, respectively) as possible. In the USA, GHG emissions from electricity generation accounted for 33 % of total GHG emissions in the year 2009, making electricity generation the single largest American source of greenhouse gas emissions (EPA 2011a). Most of these emissions come from coal-fired power plants. The US EIA reports that in 2009, 44.5 % of the electricity in the USA was produced by coal-fueled power plants, constituting the largest fossil source of electricity, and the corresponding greenhouse gas emissions make up approximately 80 % of the total greenhouse gas emissions from electricity generation in this year (EIA 2011a).

In recent years, a number of LCAs of US coal power have reported ranges of possible life cycle emissions (Jaramillo et al. 2007; Venkatesh et al. 2012b; Burnham et al. 2011; Littlefield et al. 2010; Weber et al. 2010). However, the drivers of these ranges are unclear, as the underlying analyses took into account both variable and uncertain parameters without separating the two. Moreover, these ranges were calculated via different methods. Therefore, one cannot compare these ranges with each other in a statistically meaningful way, nor identify possible ways, if any, to reduce them.

In this paper, we present a novel approach that allows for the characterization of both uncertainty and variability separately. This separate assessment allows the researcher to identify ways to improve the precision of assessments of power generation technology as well as changes in practice that may reduce heterogeneity of actual life cycle emissions. In our approach, both spatial variability and technological variability were accounted for as well as decision rule uncertainty and parameter uncertainty; temporal variability in emissions was covered only to a limited extent. Influence of spatial variability among transport distances from mine to plant was quantified on an individual power plant level, as were spatial differences in coal characteristics (e.g., carbon content) at the level of the mines. Technological variability in (1) mine type (surface vs. underground), (2) mode of transport (e.g., truck or rail), and (3) power plant efficiency was also assessed. Decision rule uncertainty regarding the choice of time horizon in the global warming potential (GWP) of methane was quantified via discrete choice analysis in conjunction with our general approach. Lastly, parametric uncertainty associated with the mining, transport, and use phases (e.g., electricity use during mining and fuel use during transport) was quantified via Monte Carlo simulation.

2 Methods

2.1 System description

The life cycle of coal from "mine to wire" is illustrated in Fig. 1. We divided the life cycle into three stages, following the convention of other LCAs (Burnham et al. 2011; Littlefield et al. 2010). In the extraction stage, coal is obtained via surface or underground mining. This phase includes activities such as methane venting, dewatering, mechanical transportation of coal to rail cars, etc. The transportation phase includes all operations associated with the transportation of coal from a mine to a power plant, including the operation of diesel locomotives and barges. The end of the coal life cycle is a power plant. There, coal is burned to yield carbon dioxide and water vapor, as well as the electricity that defines the functional unit of the LCA. We employed a functional unit of 1 kWh of electricity generated at a plant or plants in a particular calendar year. In the forthcoming example, we applied our methodology to the US coal power fleet in 2009.

We utilized two types of system boundaries: one for each "individual plant" life cycle and a second for the "comprehensive" life cycle of coal-fired power plants in the USA. Each individual power plant life cycle was defined by a single power plant and all mines that supply its coal, as illustrated by the dashed green line in Fig. 1. Thus, there are as many of these life cycles as there are power plants. The "comprehensive" life cycle boundary includes all mines and plants and is illustrated by the dark blue line in Fig. 1. Impacts associated with the two types of life cycles were used to define the uncertainty and variability associated with the carbon footprint of coal power.

2.2 Data

A key input for our approach was the data set reported by the US EIA in its annual EIA-923 Time Series File (EIA 2011b). The file includes an extensive amount of actual data reported by power plant operators. Data include receipts of coal delivered from specific mines to each power plant throughout the calendar year, the locations of coal power plants and mines, and the heat input (higher heating value, HHV) and net power output of each plant. These data are broken down by each coal type (bituminous coal, sub-bituminous coal, and lignite). The extent of information published in the EIA data file may serve as the "backbone" of any LCA of coal power generation process in the USA as it provides the sources and amounts of all coal burned at a plant from "mine to wire."

In the implementation of our approach, we conducted an assessment of carbon dioxide and methane emissions associated with US coal power in 2009. These emissions were aggregated with the GWP reported by the IPCC AR4 (IPCC 2007). For the purposes of constraining our analysis to de facto base load power plants, we restricted our analysis to 364 coal power plants that generated at least 50 MW on average for nine or more months throughout 2009 (EIA 2011b)—a criterion similar to that employed by the EcoInvent database (Dones et al. 2007) (run time >8,000 h). To avoid errors caused by unclear allocation of emissions, all combined heat and power (CHP or "cogen") plants were left out of the analysis.

In 2009, approximately 5 % of all coal (on a mass basis) was extracted from mines that utilize both surface mining and underground mining. The EIA 923 data file does not report the mining type for an additional 5 % of the extracted coal. In such cases, we used the fractions of surface and underground

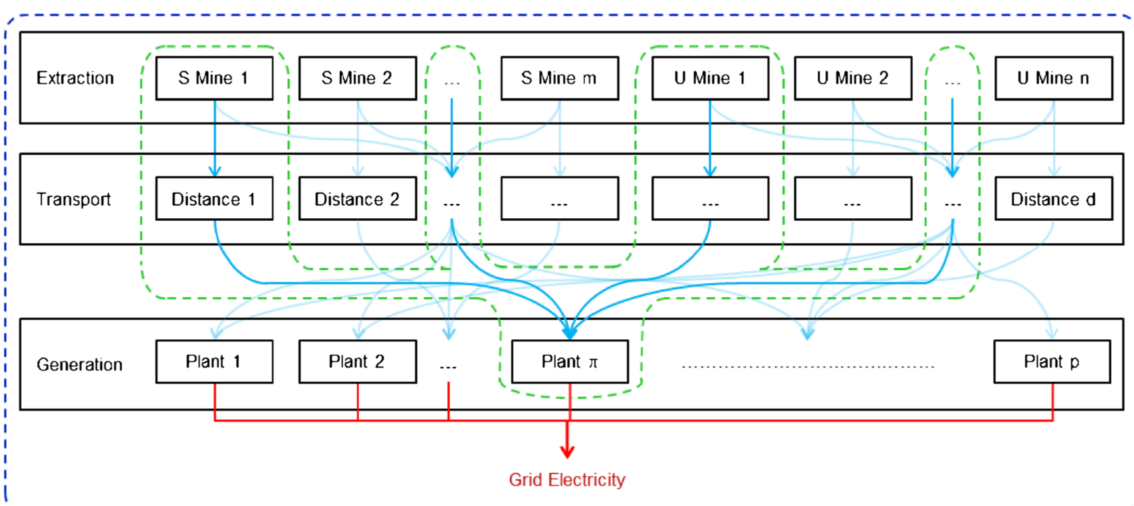

Fig. 1 Life cycle model for electricity generation from coal in the USA, including boundaries (*dashed lines*), flows of material (*light blue arrows*), and electrical output at the power plant (*red*). Variability by mine, transportation, and operation of power plants (surface (*S*) vs. underground (*U*) mining) is represented by *horizontal boxes* at each stage of the life cycle. A life cycle boundary corresponding to plant π is defined by the *dashed green line*: The plant is supplied by "surface mine 1," "underground mine 1," and several other mines

production for the mine counties to approximate the relative amounts of coal extracted via the two techniques (EIA 2010).

Fuel use for underground and surface mining was estimated from data provided in the US economic census of 2002 (US Census Bureau 2011) (see Electronic Supplementary Material 1.1 for more detailed information). Electricity use during mining for both surface and underground mining was calculated from results published by Jaramillo et al. (2007). Emissions from provision of electricity in the mines were taken from the US EPA eGRID database at a US national level (EPA 2010). Fuel use per ton-kilometer of coal transport was adopted from the EcoInvent database (Spielmann et al. 2007) for transport of coal by diesel train, truck, barge, and freight ship.

We included uncertainty in many of the parameters associated with the models of individual power plant and "comprehensive" coal life cycles. Each such parameter was implemented with Crystal Ball as a distribution defined by statistics from the literature. Parameters are available as Electronic Supplementary Material. Foreground parameters on a national level are reported in Table S1, foreground parameters on a state- or coal basin-specific level are reported in Table S2, and background parameters (all on a national level) are reported in Table S3. Most parameters that exist on the range $[0,\infty)$ were modeled as log-normal random variables to prevent inadvertent MC selection of negative parameters. This skewed distribution is often appropriate for emission factors and other parameters employed in LCA (Huijbregts et al. 2003). Parameters existing within positive finite ranges, such as fractions, were modeled with the beta-pert distribution—a continuous distribution akin to the triangular distribution specified by minimum, maximum, and "most likely" values.

2.3 General model

For each individual power plant life cycle, we calculated the carbon footprint as follows: First, we assessed the greenhouse gas emissions associated with the mining of each quantity of coal transported to the power plant. The EIA data file reports the type of mine (surface or underground) as well as the location. Using this information, we assessed mine methane emissions using additional information from the US EPA and US EIA (EPA 2011a; EIA 2011b), which is explicitly dependent upon the mine region and mine type (EPA 2011b). Uncertain parameters associated with the extraction phase (including methane emissions) were modeled as random numbers, with distributions conforming to data or engineering judgment. For instance, methane emissions (kilograms CH_4 per ton of mined coal) were modeled as lognormal distributions with means and standard deviations reported by EPA. All impacts associated with mining were calculated on the basis of the coal sent to a specific plant, including mine operations, commissioning, and decommissioning.

Next, we assessed the impacts associated with transportation. Most coal utilized for power generation in the USA is transported directly from the mine to the power generation plant via rail transport (McCollum 2007) although other types of transport include river barges, trucks, and interoceanic freight ships. In the modeling of rail transportation, we have supplemented the mine location information in the EIA 923 data file with the EIA 860 data file from 2009, which reports locations of most power plants (EIA 2011c); other power plant locations were identified via web search. EIA provides locations of mines and plants as ZIP codes, states (e.g., for collections of coal from small mining operations), and in some cases, nations (e.g., the locations of foreign mines). These were converted into geographical coordinates using information published by the US Census Bureau (2010), which includes the latitude and longitude of ZIP codes, states, and nations and their land areas. Rail distances between mines and plants are equivalent to road distances due to the historical evolution of road and rail transportation in the USA. Therefore, mine-plant rail transportation distances in the USA were estimated via the Google Map API that calculates road distances. Uncertainty in these distances was also quantified according to the methodology described in Electronic Supplementary Material 2.3.

The power generation stage of the coal life cycle requires two key calculations: calculation of the GHG emissions and calculation of the energy output. Emissions were estimated via converting the amounts of coal arriving at the plant into heat inputs and multiplying these by the carbon intensities of bituminous coal, sub-bituminous coal, and lignite. For assessments of coal power in the USA at a state level, we recommend the use of the carbon contents reported by Hong (Hong and Slatick 1994). We refer the interested reader to the online supporting information for more detail regarding US states and their corresponding coal basins.

The power generated at the plant was directly taken from the EIA 923 data file (for all coals). The actual operating efficiency of each plant in the USA was calculated from data in the file from

$$\epsilon_\pi = \frac{P_\pi}{Q_\pi} \tag{1}$$

where ε_π is the net power generation efficiency of plant π [in megajoules of net electricity per megajoule heat, HHV basis], P_π is the net power generation from coal at plant π (in megajoules of electricity), and Q_π is the total coal consumption for plant π (in megajoules of heat, HHV basis). A valuable aspect of this approach is that it yields the actual operating efficiencies of operating plants.

We simultaneously calculated the carbon footprints for all individual power plants $\pi=1\ldots p$ as well as the comprehensive life cycle via MC. Each MC simulation is akin to an experiment wherein each uncertain parameter takes on a

random value, in accordance with data or a known distribution. Calculations of the carbon footprints were conducted as follows: For each plant π, we conducted a mass balance on all supplied coal to determine impacts associated with its mining and transportation steps. Next, we calculated impacts and power output at the power plant. Finally, we summed the GHG emissions associated with all phases and normalize the sum by P_π, yielding the carbon footprint of an individual power plant life cycle in kilograms of CO_2eq per kilowatt hour. We denote this individual plant life cycle by the variable y_π.

The footprint of the "comprehensive" system (i.e., the dashed dark blue line of Fig. 1) was calculated as follows:

$$Y = \frac{\sum_\pi y_\pi P_\pi}{\sum_\pi P_\pi} \qquad (2)$$

where P_π is the power output of plant π (in kilowatt hour), and y_π is the carbon footprint of its corresponding life cycle (in kilograms of CO_2eq per kilowatt hour).

The MC selection procedure was repeated N times, generating p sets of N values representing each individual power plant footprint $\{y_{\pi n}\}$, π=1… p; n=1… N as well as one set of N values for the comprehensive footprint $\{Y_n\}$, n=1… N. The two sets are distinct in their interpretations: Statistics calculated from $\{y_{\pi n}\}$ are equivalent to those one would obtain from an analysis that considers variability as equivalent to uncertainty, e.g., an analysis that considers power plant efficiency as a random variable. Statistics calculated from $\{Y_n\}$ only capture the effects of uncertainty on the carbon footprint of all US coal-fired electricity.

The number of MC simulations required to generate these sets (N) depends upon features of the system including the number of uncertain parameters in a particular assessment, the extent of variability among power plant efficiencies, and other technological features of the supply chain. We used a sample size of N=1,000 runs; the difference in uncertainty ratio for all 364 plants was <1 % from a test run with 10,000 iterations (data not shown).

2.4 Quantification of variability

The expectation value of each set of MC simulations corresponding to an individual power plant's life cycle π (i.e., the arithmetic mean $E(y_\pi)=N^{-1}\Sigma_n y_{\pi n}$) estimates the actual life cycle GHG emissions. In the absence of parametric uncertainty, it would be the true value. Hence, variability was expressed in terms of the set of average GHG emissions $E(y_\pi)$, π=1… p. We express variability in terms of a "variability ratio," which can be interpreted as a metric for interplant variation.

$$r = \frac{q_{0.975}(\{E(y_\pi)\})}{q_{0.025}(\{E(y_\pi)\})} \qquad (3)$$

where the numerator is the 97.5th percentile of $\{E(y_\pi)\}$ (set of π=1… p), and the denominator is the 2.5th percentile. Because our set included 364 power plants, the 2.5th and 97.5th percentiles do not refer to two specific plants. The percentiles were calculated with the Excel function PERCENTILE.INC.

2.5 Quantification of uncertainty

We considered two types of uncertainty in our method: parametric uncertainty and decision rule uncertainty. Each of these "uncertainties" must be addressed differently. Decision rule uncertainty is conceptually a matter of "uncertainty" in the value choices of individual researchers. In the framework by Huijbregts (1998b), it differs from model uncertainty in that it does not reflect incomplete knowledge of the workings of nature, but rather incomplete knowledge about the values of the intended user of the knowledge. Therefore, different values may therefore be assessed via scenario analysis.

In the carbon footprinting of coal power, a key value choice is that of the time horizon for the GWPs: 20, 100, or 500 years. Recently, there has been considerable debate regarding the appropriate choice of the "time horizon" for GHG emission studies (MIT 2011). GWP is defined as the quotient of the absolute global warming potential (AGWP) of a GHG and the AGWP of carbon dioxide (IPCC 2007), where each AGWP is a measure of radiative forcing associated with these molecules. Therefore, the GWP of CO_2 is 1 for any time horizon and has no uncertainty, but the GWP of methane depends upon the time horizon and also exhibits parametric uncertainty due to uncertainties in the AGWPs of methane and CO_2. To analyze the decision rule uncertainty, we calculated our LCA results for three different time horizons of 20, 100, and 500 years.

Parametric uncertainty may result from the statistical summarization of variability, e.g., estimation of emission factors from different mines within a geographical region. Alternately, it may result from imprecision in measurement. In practice, it is introduced to LCA by way of using non-site-specific or non-process-specific parameters in models of process stages.

Differences among the MC-generated values of y_π result from parametric uncertainty. Uncertainty in the carbon footprint of an individual coal-fired power plant was quantified as

$$\rho_\pi = \frac{q_{0.975}(\{y_{\pi n}\})}{q_{0.025}(\{y_{\pi n}\})} \qquad (4)$$

where the numerator is the 97.5th percentile of the MC simulation results (set of n=1… N) for power plant π, and the denominator is the 2.5th percentile. The percentiles were calculated with the Excel function PERCENTILE.INC.

An uncertainty ratio for the carbon footprint of US coal-fired electricity, which we denote by ρ , may be calculated by

substituting $\{y_{\pi n}\}$ (the set of MC results for the life cycle emissions for power plant π) for $\{Y_n\}$ (the set of MC results for the life cycle emissions for all coal power in the USA) in Eq. (4).

2.6 Distinguishing uncertainty from variability

The parameters r and ρ share certain features that assist in the interpretation of their values: If $r=1$, then there is no effect of variability upon the results of the LCA; if $\rho=1$, then there is no effect of uncertainty upon the results of the LCA. The two statistics are analogous to the sums of squares compared in ANOVA. Insofar as $\{y\}$, $\{Y\}$, and $\{E(y)\}$ are different types of sets with different sizes and statistical properties, no statistical hypothesis test for the comparison of r and ρ can be formulated in terms of commonly utilized distributions employed by statisticians. For the practitioner, it will often be sufficient to note the relative magnitudes of these quantities: If $r>\rho_\pi$ for all power plants (π), then variability is the primary cause of the range of life cycle emissions: Further research will not reduce the range substantially; rather, physical changes must occur to reduce the range. If $r<\rho_\pi$ for all power plants (π), then uncertainty is the primary cause of the range of life cycle emissions. In this case, additional research may reduce the range of life cycle GHG emissions, e.g., improvement in the precision of emission factors.

2.7 Identification of key parametric uncertainties

If one wishes to reduce the range of the carbon footprint of coal power via reduction of uncertainty, one must evaluate the sensitivity of the final results with respect to the uncertain parameters. This was accomplished via sequential perturbation of each uncertain parameter, e.g., variation of its value between its 2.5th and 97.5th percentiles and observing the effect upon the comprehensive footprint Y. The effect of each uncertain parameter may be visualized by way of a tornado diagram, which reports both the upper and lower values of Y corresponding to perturbation of each uncertain parameter. This process is automated by software packages such as @RISK and Crystal Ball; we employed the latter of these for our analysis. Uncertain parameters yielding the largest ranges in variation of Y are those that contribute the greatest uncertainty in the LCA, for the case that all other parameters are at a constant value.

An underlying assumption of this approach is that uncertainties in parameters are uncorrelated. In the case of the LCA of coal power, parameters may generally describe unrelated processes, e.g., methane release fractions and fuel use for rail transportation. Therefore, we believe this assumption is reasonable.

2.8 Scenario analysis

Our method for carbon footprint estimations considering individual plants can be used to assess the effects of emission reduction measures on the carbon footprint of coal-fired electricity generation. Because the emissions and efficiencies of every single plant are modeled separately, it is possible to assess the influence of improving individual plant efficiencies or changing fuel type on the overall carbon footprint. Uncertainty is also propagated throughout the life cycles of the individual power plants; therefore, it is also possible to quantify the effect of changing the parameters of *any subset* of the plants on the total uncertainty, which would not be possible without separate plant life cycles. We performed three scenario analyses to illustrate how our approach can be used to assess the potential for reduction of the carbon footprint.

3 Results and discussion

3.1 Differentiation of uncertainty from variability

In Fig. 2, we present the results of MC simulations of all individual power plant life cycles of coal in the USA. Please keep in mind that our data are representative for the 2009 fleet. Temporal variability is only addressed on the level of power plant efficiencies and is discussed in Electronic Supplementary Material 5.3. We illustrate the medians and 95 % confidence intervals, sorted via the medians of the GHG emissions of the particular life cycles. By contrast, medians (and 95 % confidence intervals) of the GHG emissions of the comprehensive life cycle were 1.12 (1.08–1.19), 1.06 (1.04–1.08), and 1.03 (1.02–1.05)kg CO_2eq/kWh for the 20-, 100-, and 500-year time horizons, respectively. At a 100-year time horizon, our results are comparable to the results of Littlefield et al. (2010) (1.1 kg CO_2eq/kWh) and Dones et al. (2007) (1.2 kg CO_2eq/kWh), among others.

At a 100-year time horizon, the lowest average life cycle GHG emission was 0.92 kg CO_2eq/kWh, whereas the highest average life cycle GHG emission was 2.57 kg CO_2eq/kWh. Average emissions for the 2.5th and 97.5th percentile power plants (the x-axis range) were 0.97 and 1.69 kg CO_2eq/kWh, respectively, yielding a variability ratio of $r=1.76$. By contrast, the uncertainty ranges from individual power plants (ρ_π) varied from 1.04 to 1.2 (100-year time horizon). The life cycles with higher uncertainty ratios are those that utilize fuel sourced from outside of the USA—transportation contributes a larger fraction of the total GHG emissions for these life cycles due to longer transportation distances. Moreover, those distances have greater uncertainties than intracontinental rail distances. The uncertainty ratio for the comprehensive life cycle was $\rho=1.05$. An advantage of our plant-level-based method is that any subset of plants may be readily analyzed,

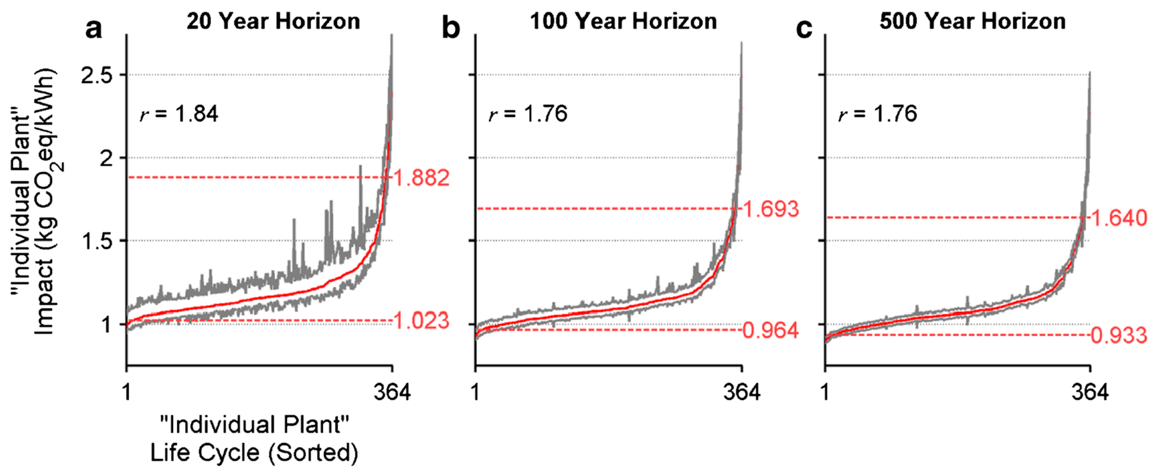

Fig. 2 Life cycle GHG emissions (in kilograms of CO_2eq per kilowatt hour of electricity generated) for life cycles defined by individual power plants and the mines that supply them. The width of each plant's uncertainty distribution (95 % interval) is delineated by *black points*, whereas the median is highlighted in *red. Horizontal red dashed lines* represent the 95 % variability intervals

e.g., plants residing in different regions. We report the carbon footprints for coal power generated in the North American Electric Reliability Corporation (NERC) regions in Electronic Supplementary Material 5.2.

In Fig. 3, we illustrate the relationship between the average life cycle GHG emissions of individual power plants (100-year time horizon) and their net generation (in megawatt hours). As a trend, life cycle GHG emissions decrease with respect to increasing net generation. Moreover, the variability for a given annual generation also decreases with generation. These trends are primarily explained by power plant efficiency: Plants with high net generation tend to have relatively high power plant efficiencies. Differences among coal types are also evident. Plants that run exclusively on lignite tend to have higher GHG emissions than those that exclusively utilize bituminous coal. The difference in GHG emissions can be attributed to differences in weighted average net efficiencies between the fuel types, which were 30.2, 32.6, and 33.4 % for lignite, sub-bituminous plants, and bituminous plants, respectively. In addition to this, lignite also has higher carbon content (in kilograms of CO_2 per megajoule of heat, HHV basis) than other fuel types from the same state (Electronic Supplementary Material, Table S3). The maximum difference in carbon content between lignite and bituminous coals mined in Montana is 5.2 %. Life cycles employing bituminous and sub-bituminous coals are less easily differentiated, owing to the fact that the average net efficiencies of their plants and carbon contents are similar (Electronic Supplementary Material, Table S3).

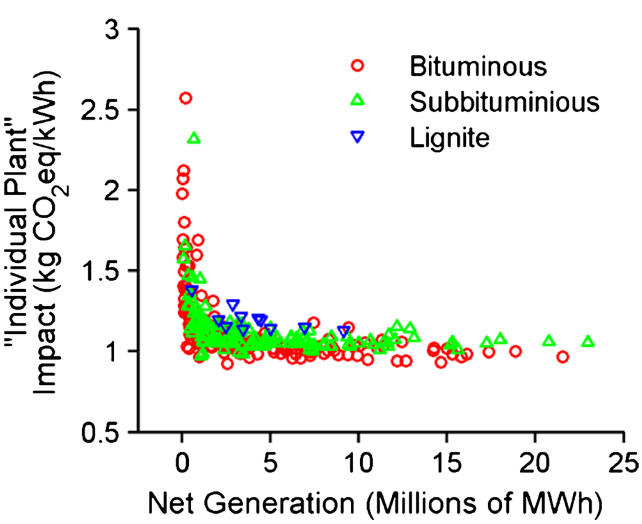

Fig. 3 Effect of coal type and power plant output upon the average life cycle GHG emissions (100-year time horizon). Increased plant capacity and generation tend to result in the reduction of emissions, largely as a consequence of improved power plant efficiency: Results of 11 lignite, 169 bituminous coal, and 127 sub-bituminous coal life cycles are illustrated

In Fig. 4, we illustrate the relative contributions of uncertainty and variability to the coal power footprint. In Fig. 4a, we show the complete distribution of the life cycle GHG emissions from coal power ($\{y\}$), which includes both uncertainty and variability. When uncertainty is removed, the resulting set of life cycle emissions ($\{E(y)\}$) has a very similar distribution; indeed, the 10th and 90th percentiles of the data constituting Figs. 4a, b are indistinguishable. By contrast, when variability is removed from $\{y\}$, the relatively small impact of uncertainty is evident. From these results, we may conclude that life cycle variability is the key driver of the range of life cycle GHG emissions from coal power.

3.2 Key parametric uncertainties

In Fig. 5, we illustrate the sensitivity of the comprehensive footprint with respect to uncertain variables. The comprehensive coal footprint was sensitive to the uncertainty in the absolute GWPs of methane and CO_2: their ratio constitutes

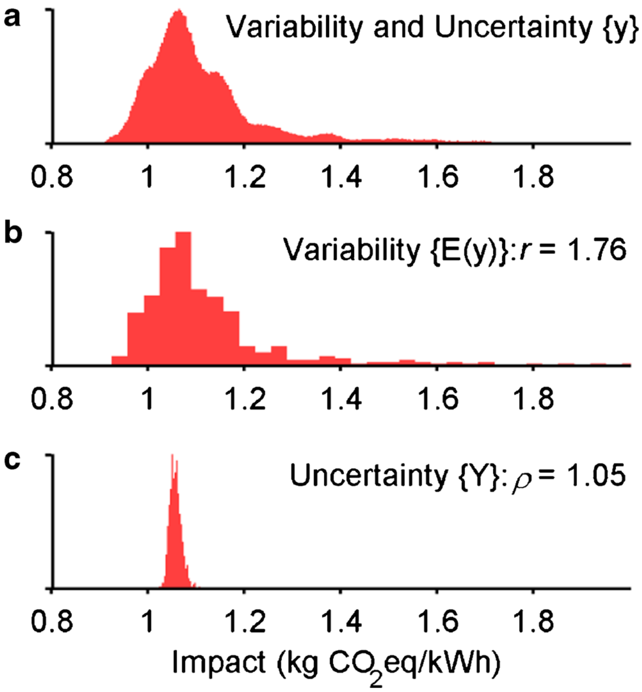

Fig. 4 Variability is the primary cause of the range of life cycle emissions associated with coal power in the USA. **a** Histogram illustrating 1,000 MC simulations of 364 coal life cycles defined by coal plants in 2009 and the mines that provided their fuel. **b** Histogram illustrating average life cycle emissions of the aforementioned systems. **c** Histogram illustrating 1,000 MC simulations of the US coal footprint

the GWP of methane, which is a significant GHG emission source in the upstream phase of the coal life cycle.

Sensitivity of the carbon footprint to uncertainties in factors associated with the mining of sub-bituminous coal from Wyoming reflects the significance of this coal in the US supply (about 20 % by mass). Even though the uncertainty in the carbon content is relatively small, the large share of this coal source to the total supply made the influence of this parameter on the footprint relatively large.

3.3 Decision rule uncertainty

Decision rule uncertainty was analyzed over three different time horizons, revealing that the ratio between the median footprints at the 20- and 500-year time horizons is 1.09: a slight decrease in the life cycle GHG emissions of coal power generation was observed with increasing length of the time horizon. The decrease was a consequence of the fact that the GWP of methane decreases with time. The small effect of decision rule uncertainty is due to the fact that the vast majority of the GHG emissions originate from the power generation and transportation stages of the coal power life cycle where mainly CO_2 is emitted—methane emissions constitute a small fraction of the total emissions. Parameter uncertainty and variability in the life cycle GHG emissions at time horizons of 20 and 500 years were similar to those of the 100-year time horizon.

3.4 Upstream contributions to life cycle GHG emissions

For a 100-year time horizon, upstream emissions (mining and transport phase combined) accounted for 6 % of the total life cycle GHG emissions for US power generation with the 95 % uncertainty interval ranging from 5 to 9 % The upstream contribution of 8 % reported by the NETL LCA of coal power (Littlefield et al. 2010) is well within this range. The relative contribution of upstream emissions was larger for the 20-year time horizon with an average value of 12 % (95 % interval, 8–17 %) and smaller for the 500-year time horizon average of 4 % (95 % interval, 3–6 %). Additional information is provided in Electronic Supplementary Material 5.1 (Fig. S1 A–C). The difference between results at these time horizons reflects the relative importance of methane emissions, already discussed. The relatively large uncertainty intervals reflect the larger uncertainty in input data for the upstream phases, compared to the uncertainty in use phase parameters. The 97.5th

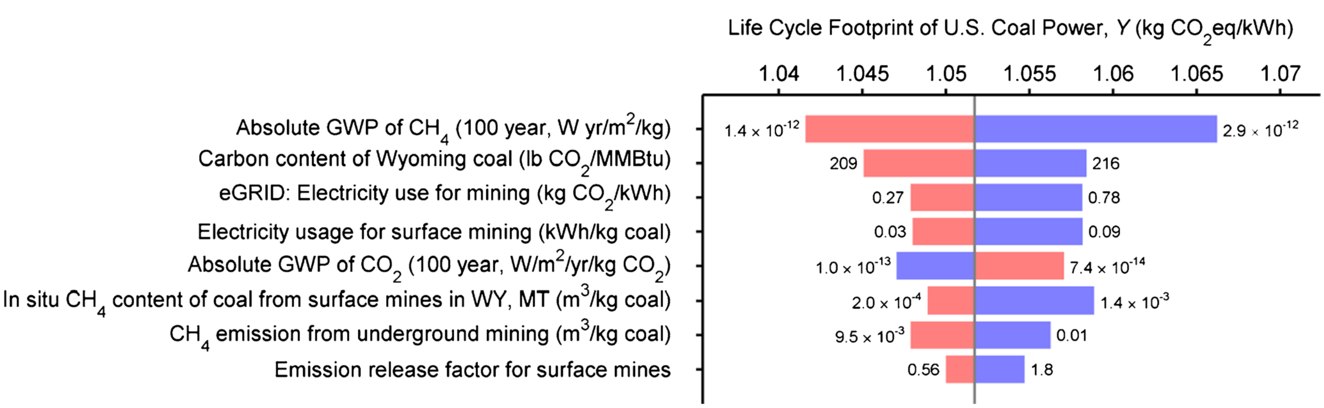

Fig. 5 Sensitivity of comprehensive coal power footprint to uncertain parameters. *Blue bars* indicate higher than average values of the parameters, and *red bars* indicate values that are below the average

and 2.5th percentiles of average upstream contributions of individual power plant life cycles differed by a factor of four: evidence of relatively large variability in upstream emissions compared to the variability in the total life cycle GHG emissions. The relatively large variability in GHG emissions in upstream processes, such as coal transport, contributes little to the variability in the overall carbon footprint. This can be explained by the fact that GHG emissions of upstream processes are relatively small compared to the GHG emissions during the use phase per functional unit.

3.5 Comparison with other studies

Our study is the first to delineate uncertainty from variability, but other studies do report ranges of emissions. "Range ratios" akin to r or ρ calculated from previously reported studies (Jaramillo et al. 2007; Burnham et al. 2011; Dones et al. 2007) vary from 1.4 to 1.1 and include both uncertainty and variability. The difference is primarily attributable to the larger overall range of power plant efficiencies predicted from the EIA 923 data set: 13.5 to 36.8 % HHV (minimum–maximum). By contrast, the Argonne GREET model (Burnham et al. 2011) uses a *theoretical* power plant efficiency range of 33.5–34.4 % for conventional coal plants, and the 2007 study of Jaramillo et al. (2007) used a range of 30–37 %. Venkatesh et al. (2011) have recently updated the Jaramillo study and considered power plant efficiency as a random variable ranging from 24 to 37 % (90 % interval) based on the EPA eGRID data set from 2006. This range is similar to the 90 % interval in our data (24–35 %). It should be noted that the efficiency to be selected also depends on the goal of the study. If the average carbon footprint of coal power in the USA is of primary interest, then the average efficiency may be suitable. By contrast, if the prediction of GHG emissions of new coal-fired power plants is the point of inquiry, then a relatively high plant efficiency may be more suitable. For the analysis of the total variability in plant emissions, however, our approach of using the actual plant efficiencies (rather than a theoretical estimate) is preferred. As the range of efficiencies increases, one expects a larger value of r. As our results show, the variability of the emissions is tantamount to the range owing to the relative disparity between uncertainty and variability.

3.6 Scenario analysis

Our results indicate that a reduction of the range of the coal power footprint requires a reduction in variability. The two most important sources of variability are in coal type and power plant efficiency. The average efficiency for coal-fueled power plants in the USA was 32.9 %. If all US plants had this efficiency, then r would decrease from 1.76 to 1.2. The remainder of the variability is due to differences in transportation and mining type. Changes in these types of variability require large changes in the fuel market as well as large technological changes in power plant operations. Without considering *how* such changes might be implemented, we considered the following scenarios:

A. All coal power plants operating below 32.9 % HHV (the 2009 average) in 2009 operate at 32.9 % HHV.
B. All coal power plants operating below 35 % HHV (95th percentile in 2009) in 2009 operate at 35 % HHV.
C. Total power production allocated to plants that utilize bituminous coal only.

Scenarios A and B were chosen to investigate the effects of raising the efficiencies of poorer performing plants. Scenario C was chosen to investigate the effect of excluding the least efficient fuel type. We evaluated these effects in the context of a 100-year time horizon.

In scenarios A and B, the total life cycle GHG emissions were reduced by approximately $3.8 \cdot 10^{10}$ and $1.1 \cdot 10^{11}$ kg CO_2eq/year, respectively. Scenario C reduced the emissions by $4.3 \cdot 10^{10}$ kg CO_2eq/year. In scenarios A, B, and C, the base case total GHG emissions were reduced by 2.1, 6.0, and 2.4 %, respectively. The maximum achievable reduction of 6 % in the most ambitious scenario does not take into account the feasibility of this scenario. Venkatesh et al. (2012a), who have analyzed the practical aspects of implementing coal plant retirement scenarios in more detail, found a maximum feasible emission reduction of about 4 %.

3.7 Model limitations and alternatives

While we put much effort in disentangling uncertainty and variability, it is not always feasible to completely do so. In our modeling approach, we specified parameters as uncertain, even though the influence of variability could not be fully excluded. An example is the diesel use in coal-transporting trains, which is modeled as an uncertain parameter. The fuel use per ton-kilometer may, however, also depend on spatially (or temporally) variable parameters such as whether the route from mine to plant is uphill, downhill, or flat and the average wind speed.

In our study, we observed that the uncertainty ratios are much smaller than the variability ratios. We therefore conclude that the influence of possibly overestimating uncertainty ranges of input parameters on our results is most likely limited. This may, however, not always be the case in LCA and should be studied on a case-by-case basis.

In our approach, we applied Monte Carlo simulation to quantify the uncertainty. Another approach to analyze the simultaneous influence of several uncertain parameters throughout the entire life cycle is analytical error propagation. The analytical error propagation approach may require less computational power than Monte Carlo (Ciroth et al. 2004), especially for less complex systems. This approach might be used in our model framework as well.

4 Conclusions and recommendations

We have demonstrated that the variability in the carbon footprint of US coal-fueled electricity generation is much larger than the uncertainty found for any of the 364 examined power plants. An important implication of this result is that obtaining more accurate estimations of uncertain parameters will do little to improve the accuracy of a deterministic LCA. Instead, we advise LCA practitioners to consider incorporating variability in their LCAs as a range of possible emissions and/or plant efficiencies. It is particularly important to account for variability in GHG emissions from coal-fired power plants in LCA studies when electricity is sourced from one or a few known coal-fired power plants; this may be the case for some large industrial consumers. In such cases, estimates of the carbon footprints of products manufactured with this coal-generated electricity may be substantially under- or overestimated if an average value is used for the carbon footprint of coal-fired electricity. Furthermore, we have also shown that the potential for reduction in total coal GHG emissions in the USA is about 6 %, even under the very optimistic assumption that all plants can obtain a net efficiency of 35 % or higher.

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